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Influencing factors and fluctuation characteristics of China's carbon emission trading price

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HIGHLIGHTS

- Influencing factors of China's carbon emission trading price are investigated.
- Fluctuation characteristics of China's carbon emission trading price are explored.
- There is a long-term equilibrium relationship between price and factors.
- Return series are consistent with the characteristics of financial time series.
- There is a positive leverage effect for the price fluctuations.

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ABSTRACT

The environmental deterioration and resulting climate change have become one of the major challenges that human has faced in recent years. Carbon emission trading, as an effective economic tool to deal with climate change issues, has attracted widespread attention. As a major carbon emitter, China plays an important role in combating global climate change. Based on the carbon emission trading price data of China's Hubei Emission Exchange, a Vector Auto-Regressive (VAR)-Vector Error Correction (VEC) model is first used to investigate the dynamic relationship between energy price, macroeconomic indicators, air quality, and carbon emission trading price. The results show that there is a long-term equilibrium relationship between carbon emission trading price and these indicators. When the carbon emission price is too high and deviates from the long-term equilibrium value, it will slowly decline to reach the long-term equilibrium value. The price of carbon emission trading is largely affected by macroeconomic indicators among all these influencing factors. In addition, a Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model is used to explore the fluctuation characteristics of China's carbon emission trading price. It is found that the return series of carbon emission price are consistent with the characteristics of financial time series, such as fluctuation aggregates, spikes and thick tails, and non-normal distribution. There is a positive leverage effect for the fluctuation of China's carbon emission price. It is further found that external bad news has a greater impact on the fluctuation of China's carbon emission trading price than good news.

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1. Introduction

In recent decades, with the rapid development of the global economy and the increasing demand for fossil fuels, large amounts of carbon dioxide and other greenhouse gas (GHG) emission have exacerbated the greenhouse effect. How to deal with the greenhouse effect and climate issues has become one of the most complex challenges that human beings are currently facing [1,2]. According to the statistics of the International Energy Agency (IEA), global carbon dioxide emission from fuel combustion has increased from 26,177 Mt in 2004 to 32,190 Mt in 2013 [3]. Countries around the world have also gradually realized the seriousness of the climate issue. The United Nations Framework Convention on Climate Change was adopted at the United Nations Environment Development Conference in 1992. This is the first international convention in the world that deals with the adverse effects of global warming on the human economy and society through the comprehensive control of carbon dioxide and other GHG emission. Subsequently, the Kyoto Protocol was promulgated in 1997. This makes GHG emission reduction a legal obligation for developed countries. It is also these two conventions that gave birth to the carbon finance market [4,5]. In 2015, the Paris Climate Change Conference adopted the "Paris Agreement" [6]. It focuses on how to deal with climate change after 2020, which is the second legally binding climate treaty after the Kyoto Protocol [7]. In September 2016, on the opening of G20 Hangzhou Summit, China and the United States officially ratified the Paris Agreement [8]. According to the BP World Energy Statistical Yearbook data, China became the world's largest carbon emitter in 2006, and in 2009, China became the largest energy consumer [9]. With the United States announcing its withdrawal from the Paris Agreement in 2017, China, as the world's largest energy consumer and carbon emitter, will play a more important role in global climate change [8].

In order to implement the concept of green development and effectively respond to global climate change, Chinese government has taken many measures to control GHG emission. In October 2011, the National Development and Reform Commission approved the implementation of the "Twelfth Five-Year Plan" for the gradual establishment of a domestic carbon emission trading market and agreed to establish carbon emission trading pilots sites in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen [10,11]. At the end of 2017, in the attention of domestic and foreign market participants, the unified carbon trading market covering the whole country was also officially launched, and it is expected that actual transactions will begin before 2020.

Carbon emission trading is the trading and investment activities that taking "carbon emissions right" and its derivative products as the subjects. As an economic measure to deal with climate change, carbon emission trading can not only alleviate climate problems, but also promote low-cost emission reduction. In other words, participation in carbon emissions trading can enable countries to achieve their own GHG reduction targets with lower abatement costs. The specific way is that the government allocates carbon emission quota to enterprises according to their emission reduction commitments. If an enterprise emits CO_2 less than its quota, the remaining quota can be sold; and those enterprises that emit more than their quota must purchase additional quotas or pay fines [12]. Carbon trading market is the place for these financial transactions, including all the institutional arrangements and policy systems. Although China's carbon trading market structure has been initially formed, it is still in its infancy and a complete product pricing mechanism has not yet been established. The price of carbon emission trading in seven pilot markets varies greatly, and abnormal fluctuations often occur. Inadequate pricing mechanisms and unusual price volatility have increased the risk of the carbon trading market, which has caused many companies to lose their enthusiasm for entering the carbon trading market. This is not conducive to the establishment of a unified national carbon trading market. It is also difficult to achieve the goal of reducing GHG emission through carbon emission trading in the carbon trading market. Therefore, investigating the influencing factors and fluctuation characteristics of carbon emission price is conducive to reducing carbon market risks and controlling unexpected fluctuations in carbon emission price. It will help China improve its carbon trading system and establish a reasonable carbon pricing mechanism. At the same time, it will also attract more enterprises to participate in carbon emissions trading, contributing to the establishment and operation of the national unified carbon trading market and achieve the goal of reducing GHG emissions through carbon emissions trading.

Therefore, this study provides an empirical analysis based on the carbon trading price and related data of the China's Hubei Emission Exchange. Considering the carbon emission rights as a kind of commodity, the price fluctuations are affected by some other external factors. The changes in supply and demand situation in carbon market will affect the trading price of carbon emission rights. We focused on the influence of energy price, macroeconomic development levels, air quality and industrial development levels on carbon emissions and carbon emission trading price. To further understand the characteristics of the carbon trading market and price fluctuation, we also investigate the fluctuation characteristics of carbon emission trading price. It also provides some policy implications for reducing carbon market risks, establishing a unified national carbon market pricing mechanism, and improving the carbon emission trading system. These will help China establish a reasonable pricing mechanism for carbon emission and further improve the carbon emission trading system in the future. In addition, it also provides some references for avoiding market risks and controlling the unanticipated fluctuations in carbon emission price. As the world's largest developing country, China can play a more important role in global carbon market development. Therefore, this study also provides some implications for some other developing countries to establish a unified carbon emissions trading market.

The remainder of this paper is organized as follows. Section 2 summarized relevant research works. In Section 3, the methods are introduced. In Section 4, we discuss the results of influencing factors and fluctuation characteristics of China's carbon emission trading price. Section 5 provides conclusions and some policy implications.

2. Literature review

China's carbon market started late and is still in its infancy. The national unified carbon emission trading market has not officially begun to operate. For the operation of seven trading pilots, some domestic and foreign scholars have conducted research. According to the results of an online survey conducted by Yang et al. [13], it was found that carbon emission price were not effective in stimulating enterprises to improve emission reduction technologies. Enterprises participate in carbon emission trading, mostly as a mean to improve relations with governments and obtain social reputation, rather than as an effective mechanism to reduce GHG emission. Fan et al. [14] used the Computable General Balance (CGE) model to study the impact of the domestic carbon trading market on economic development and carbon emission efficiency in different regions. As a result, it was found that the carbon market could effectively reduce the cost of the entire society. At the same time, it could improve the efficiency of social welfare and the allocation of production factors, narrow the regional economic gap and cooperation, and facilitate the coordinated development of regional economies. Munnings et al. [15] evaluated the operation plans of the three carbon trading pilots in Guangdong, Shanghai, and Shenzhen. They found that the trading mechanism design of these three pilots was fully consistent with China's national conditions. Jiang et al. [16] focused on the regulatory framework of Shenzhen's carbon emission trading, and concluded that its design has a great influence in coordinating the dynamic relationship between economic growth, industrial restructuring, and controlling emissions. Zhao et al. [17] evaluated the efficiency of China's carbon market based on the theory of effective market hypotheses. The results showed that China's carbon market was in an immature emerging stage, only reached the weak-form efficiency. With the increase in market size and trading volume, China's carbon market efficiency would become more effective.

With the gradual development of carbon trading market at home and abroad, some scholars have also conducted relevant research on the factors that affect the trading price of carbon emission. Zou and Wei [18] found that Certified Emission Reduction (CER) spot price were positively affected by macroeconomic indicators (industrial production index) and climatic indicators (surface monthly average temperature differential value) by establishing VAR and VEC models, and it were also significantly affected by futures price. Chen and Wang [19] analyzed the supply, demand, and market from the perspective of theoretical analysis. They believed that the supply of policies and institutional quotas was the most important factor affecting the European Union Allowance (EUA) price. In addition, energy price were also the influencing factor, while the effects of weather factors such as temperature and precipitation were not obvious. In the research on the influencing factors of China's carbon trading price, Yu and Wang [20] used the analytic hierarchy process to conduct empirical research. From the aspects of market, technology, ecology, and policy management, 19 major factors affecting China's carbon trading price were selected for analysis and evaluation. By determining the weight of each factor, they found out the most important factor affecting China's carbon trading price. The results showed that the top five influencing factors were the number of EU quotas, the actual emissions of each country, the changes in the international system, and the certification standards for transactions and carbon credits. Zhou and Xu [21] conducted research on the impact of factors including energy price, macroeconomic indicators, climate, and foreign carbon emission price on domestic carbon emission price based on the data from China Shenzhen Emission Exchange. The results showed that the price of coal had the greatest impact on domestic carbon emission price, and the impact of air quality was also greater. The Industrial Index and CER futures price had a positive effect. The VEC model indicated that there was a reverse correction mechanism, but the speed was slow. Guo [22] used the adaptive Lasso method to analyze the price of China Shenzhen Emission Exchange, and adopted a total of 13 relevant variables including the international carbon emission price, domestic and foreign economic conditions, energy price conditions and exchange rates. The author found that the domestic carbon emission price was most affected by the exchange rate of the euro, and the impact of domestic oil price was secondary. The domestic economy and the European economic situation had a positive impact on domestic carbon emission price, and the impact of global carbon emission price and domestic carbon emission price was not obvious. Based on the data of China Hubei Emission Exchange, Li and Lei [23] presented an empirical study using the multi-time series model and ARCH model. They found that the carbon trading price was mainly affected by the energy price.

For related study of carbon emission price fluctuation characteristics, Peng [24] constructed an option pricing model based on GARCH-Fractal Brownian Motion to study the pricing of EUA carbon future options. The empirical results showed that the AR (2)-GARCH model could well describe the heteroskedasticity of carbon financial futures yield. Pricing accuracy of the research method of this paper was significantly better than Black–Scholes (B–S) option pricing method based on historical fluctuation, B–S option pricing method based on GARCH, and Fractal Brownian Motion option pricing method based on historical fluctuation. Chen et al. [25] took the influence factors of the carbon trading price in the voluntary emission reduction market as the research object, and conducted a theoretical analysis from the aspects of supply, demand and market impact. Authors used the American Chicago Climate Exchange as an empirical object, using panel regression and AR(1)-GARCH(1,1) model analysis methods. Through empirical research, it was found that the price impact factors of the first-stage contract quotas in the Chicago Climate Exchange were mainly the supply and demand of quotas, and the influence of products in different years has increased with time. The second stage is most affected by energy price, and natural gas price are the most important factors.

In the study of price fluctuations in the domestic carbon market, Zhang [26] collected transaction data from the establishment of regional carbon emission markets in seven cities to March 31, 2016, and used the GARCH model to conduct an empirical analysis. As a result, it was found that the carbon emission trading price of the regional carbon

market were in different ranges and there were large differences between them. The fluctuation of the logarithmic returns of carbon trading price between Shenzhen and Hubei province was relatively small, and affected by other unpredictable factors to a lesser degree. To a certain extent, they had the function of reflecting market information. The development of the carbon market in Shenzhen and Hubei province was more mature. Lv and Shao [27] took the "four cities and two provinces" carbon trading markets as research objects, and used the GARCH model to study the fluctuation characteristics of carbon emission trading price in China. It was found that the development of carbon emission market in various parts of the country was unbalanced, the price fluctuation characteristics of carbon emission rights in each regions were different, and the leverage effects across the country were mixed. Among them, there was a weak asymmetry effect in Shenzhen's carbon emission sequence fluctuations, and it also showed a weak leverage effect. There were significant "asymmetric effects" in the fluctuation of carbon emission rights in Shanghai and Guangdong. Cong and Lo [28] used the ARMA-GARCH-M model to study the fluctuations of carbon emission price under the Shenzhen ETS in China. They found that the return rate was negatively associated with expected risk represented by the conditional variance.

In summary, the existing research mainly focused on the carbon market regulation system, the role of the carbon market in coordinating the balanced and efficient development of the economy, and the evaluation of the operating efficiency of the carbon market. Research on carbon emission trading price mainly focused on the theoretical level. The consideration of factors affecting the carbon emission price was not comprehensive and detailed. The background of the existing research was mainly concentrated in the European market, and there was no localization treatment according to the actual development situation in China. Research on the fluctuation characteristics of carbon emission price were mainly based on the link between spot and futures, and less consideration was given to asymmetry. In addition, the existing research on the carbon market price in China are mostly based on the data of China Shenzhen Emission Exchange. In order to provide a more comprehensive reference for the upcoming national unified carbon market, data from other representative pilot exchanges need to be taken into consideration.

In light of the deficiencies in the above studies, we compared the transaction data from seven pilot exchanges in China since their establishment. It was found that the total transaction volume and total transaction amount of China Hubei Emission Exchange since its establishment was the highest. Its successful experience and existing problems may be more important for the development of the nationwide carbon market. This paper selects data from the carbon trading market of the China Hubei Emission Exchange and uses a VEC model to explore the dynamic relationship between carbon emission trading price and energy price, air quality, and macroeconomic indicators. In addition, the GARCH model is used to explore the fluctuation characteristics of the carbon emission price of the China Hubei Emission Exchange, so that the fluctuation characteristics of the carbon emission trading price can be expressed more intuitively and accurately.

3. Methods

This section describes the econometric models that will be used in the empirical studies below. First are the models which are used to study the influencing factors of the carbon emission price. (1) VAR model. An effective VAR model is a prerequisite for cointegration analysis. It is necessary to establish VAR model and determine the optimal lag order of the model before cointegration analysis. (2) Impulse Response Function (IRF). We use the IRF to analyze the effect of imposing a one-time shock on the disturbance term on the current and future values of the response variable. (3) Cointegration analysis and VEC model. The coefficient of influence of each factor can be derived by establishing a cointegration equation. According to the coefficient of influence, the degree of influence of each factor on the fluctuation of carbon emission price can be inferred. Then by fitting the VEC model, the adjustment coefficient of the error correction term is obtained. It can be used to analyze long-term adjustments between related variables. The second are the GARCH family models which used to study the fluctuation characteristics of the carbon emission price. (4) GARCH model. Through the fitting results of the GARCH model, it can be analyzed whether the impact of external good news or bad news will affect the fluctuation of carbon emission price. (5) TGARCH model. The fitting result of the TGARCH model can be used to analyze whether there is asymmetry in the influence of good news or bad news on the fluctuations of carbon emission price. (6) EGARCH model. Through the fitting results of the EGARCH model, it can be analyzed whether the good news or bad news has a leverage effect on the impact of carbon emission price fluctuations. The following is a detailed introduction of each model.

(1) VAR model

Sims first proposed the VAR model analysis method [29]. VAR models each endogenous variable in the system as a function of the lag value of all endogenous variables in the system, thus extending the univariate autoregressive model to a "vector" autoregressive model consisting of multiple time series variables.

The mathematical expression of a standard VAR (p) model is defined as

$$y_t = \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + Hx_t + \varepsilon_t, \quad t = 1, 2, \ldots, T \tag{1}$$

where y_t is the k-dimensional endogenous variable column vector, x_t is the d-dimensional exogenous variable column vector, p is the lag order, and T is the number of samples. The $k \times k$-dimensional matrix $\Phi_1 \cdots, \Phi_p$ and $k \times d$-dimensional matrices H are coefficient matrices to be estimated, and ε_t is a k-dimensional perturbation column vector. Each element is non-self-correlated, but allows correlation between different elements.

(2) IRF

In practice, the VAR mode is a model that describes the impact on the whole. It does not need to analyze the extent to which one variable affects other variables, it only examines how statically it affects the model as a whole. Therefore, IRF method was proposed [30]. The IRF describes the response of an endogenous variable to an error shock. Specifically, it describes the impact on the current and future values of endogenous variables after imposing a standard deviation magnitude impact on the random error term.

Rewrite the VAR (p) model as VMA (∞).

$$\begin{aligned} y_t &= (I_k - \Phi_1 L - \cdots - \Phi_p L^p)^{-1}\varepsilon_t \\ &= (I_k + A_1 L + A_2 L^2 + \cdots)\varepsilon_t \quad , t = 1, 2, \ldots, T \end{aligned} \tag{2}$$

The ith variable y_{it} of y_t can be written as Eq. (3).

$$y_{it} = \sum_{j=1}^{k}(a_{ij}^{(0)}\varepsilon_{jt} + a_{ij}^{(1)}\varepsilon_{jt-1} + a_{ij}^{(2)}\varepsilon_{jt-2} + a_{ij}^{(3)}\varepsilon_{jt-3} + \cdots) \tag{3}$$

The i-row and j-column element of A_q can be expressed as Eq. (4).

$$a_{ij}^{(q)} = \frac{\partial y_{i,t+q}}{\partial \varepsilon_{jt}}, \quad q = 0, 1, \ldots \tag{4}$$

Eq. (4) describes the response of $y_{i,t+q}$ to a unit impulse of y_{it} in the case that the perturbation term of the jth variable is incremented by one unit and the other perturbations are constant in the t period. We call it pulse-response function.

(3) Cointegration analysis and VEC model

There is a long-term equilibrium relationship between some economic variables. This equilibrium relationship means that there is no internal mechanism that undermines equilibrium in the economic system. If the variable deviates from its long-term equilibrium after being disturbed for a certain period of time, the equilibrium mechanism will be adjusted in the next period to bring it back to equilibrium. Although some economic variables are themselves non-stationary sequences, their linear combinations may be stationary. This smooth linear combination is called a cointegration equation [31,32] and can be interpreted as a long-term stable equilibrium relationship between variables.

This methodology is based on the following equation.

$$y_t = \alpha + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \tag{5}$$

Through the integral transformation, we can get

$$\Delta y_t = \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \Pi y_{t-1'} + \varepsilon_t \tag{6}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$, $\Gamma_i = -\sum_{j=i+1}^{p} A_j$, and Δy_{t-j} is a vector consisting of I (0) variables. Δy_t is a stationary process when and only when Πy_{t-1} is a vector consisting of I (0) variables. That is, there are cointegration relationships among $y_{1,t-1}, y_{2,t-1}, \ldots, y_{k,t-1}$. When the rank of Π satisfy the condition $0 < r < k$, it means that there are r cointegration relationships. There exists $(k \times r)$ matrices α and β which satisfies

$$\Pi = \alpha\beta' \tag{7}$$

where $R(\alpha) = r$ and $R(\beta) = r$.

Put Π into Eq. (5), it can be turned into

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \tag{8}$$

Eq. (8) requires that each row of $\beta' y_{t-1}$ is an I (0) vector, and each column is an I (0) combinational variable. Matrix β determines the number and form of cointegration vectors between y_{t-1} components. Therefore, it is called a cointegration vector matrix and r is the number of cointegration vectors.

Engle and Granger [33] built a VEC model by combining cointegration analysis with error correction models based on the VAR model. The idea embodied in the VEC model is that there may be a long-term equilibrium relationship between the relevant variables. Short-term changes in variables are a partial adjustment to this long-term equilibrium. The number of cointegration relationships between a set of $I(1)$ variables is called the "cointegration rank". For $n \times I(1)$ variables, there may be at most $n - 1$ co-integration relations.

For the VAR model with co-integrated rank h, there is the following cointegration equation.

$$y_t = \nu + \delta t + \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \varepsilon_t, \quad t = 1, 2, \ldots, T \tag{9}$$

The VEC model based on the VAR model can be written as

$$\Delta y_t = \nu + \delta t + \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{p-1}\Delta y_{t-p+1} + \varepsilon_t \tag{10}$$

In the equation, $\Gamma_s = -(\Phi_{s+1}+\cdots+\Phi_p)$, $\alpha\beta' = -(I_n-\Phi_1-\Phi_2-\cdots-\Phi_p)$. α, β are two full rank matrices. $z_{t-1} = \beta' y_{t-1}$ is an error correction term that represents the long-term relationship between variables. α is the adjustment parameter matrix.

(4) GARCH

The GARCH model was proposed by Bollerslev [34], which added q autoregressive terms to the ARCH (p) model to form the GARCH (p, q) model. It further models the variance of error terms and is therefore well-suited for analyzing and predicting fluctuation. The GARCH (p, q) model is set as

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q}^2 + \gamma_1\sigma_{t-1}^2 + \cdots + \gamma_p\sigma_{t-p}^2 \tag{11}$$

where p is the autoregressive order of σ_t^2 and q is the lag order of ε_t^2. We assume that the disturbance term ε_t is generated as

$$\varepsilon_t = \upsilon_t\sqrt{\alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q}^2 + \gamma_1\sigma_{t-1}^2 + \cdots + \gamma_p\sigma_{t-p}^2} \tag{12}$$

where υ_t is white noise. The basic setting of the GARCH (1, 1) model is expressed as

$$\text{Mean equation: } y_t = x_t y + \varepsilon_t, \quad t = 1, 2, \ldots, T \tag{13}$$

$$\text{Variance equation:} \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 \tag{14}$$

where x_t is the $1 \times (k+1)$-dimensional exogenous variable vector and γ is the $(k+1) \times 1$-dimensional coefficient vector. The mean equation obtained above is a function of the exogenous variable that contains the error term. The variance equation consists of three parts, a constant term (ω), an ARCH term, and a GARCH term.

(5) TGARCH

Engle and Ng [35] believe that the shocks in the capital market usually show a very obvious negative asymmetric effect, which means the market sensitivity to negative news is more sensitive than positive news. Based on this study, Glosten, Jagannathan, and Runkle [36] proposed the asymmetric "Threshold GARCH" model (TGARCH).

Assume that the conditional heteroskedasticity equation is as

$$\sigma_t^2 = \alpha_0 + \alpha_1\mu_{t-1}^2 + \gamma_1 d_{t-1}\mu_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{15}$$

where d_{t-1} is a dummy variable, the value is 1 when the disturbance term is negative; 0 otherwise. d_{t-1} meets the following conditions.

$$d_{t-1} = \begin{cases} 1, & (\mu_{t-1} < 0) \\ 0, & (\mu_{t-1} \geq 0) \end{cases} \tag{16}$$

Compared with the GARCH model, the TGARCH model sets up a threshold d. When the value of d is 1, it indicates the influence of good news. When the value of d is 0, it indicates the influence of bad news. γ is a parameter used to reflect the asymmetric impact of good and bad information on financial market. Significantly non-zero γ coefficient indicates that the effect of good and bad news on fluctuation is asymmetric, it means that good news has greater impact on fluctuation than bad news. On the contrary, $\gamma < 0$ means that bad news has a greater impact on fluctuation than good news.

(6) EGARCH

In the standard GARCH model, the value of the parameters is limited. Therefore, it is necessary to consider the following Exponential GARCH model (EGARCH) [37].

$$ln\sigma_t^2 = \omega_0 + \gamma\frac{\mu_{t-1}}{\sigma_{t-1}} + \alpha\left|\frac{\mu_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right| + \beta ln\sigma_{t-1}^2 \tag{17}$$

The left side of the Eq. (17) has a logarithmic form of the conditional variance, which indicates that the leverage effect will be exponential, so the predicted value of the conditional variance is also non-negative. If the leverage effect does exist, we can pass the hypothesis that $\gamma \neq 0$, and the impact of the impact will be asymmetric. At this point, the influence of the impact is asymmetric.

4. Results and discussions

4.1. Influence factors of carbon emission price

In this section, we study the influencing factors of carbon emission price. When selecting carbon emission price data, we looked at some relevant research and combined with the actual situation in China. Finally, we selected the transaction

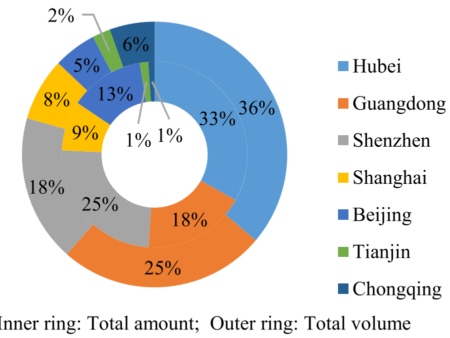

Fig. 1. Total amount and total volume of emission trading of each pilot in China [38].

data of China Hubei Emissions Exchange as carbon emission price data. When selecting the influencing factors, we selected four indicators from three aspects: energy price, macroeconomics indicators, and air quality. The specific basis for data selection in this section of the study is described below.

(1) *Carbon emission price.* This section selected the HBEA daily closing price [38] from China Hubei Emission Exchange as the carbon emission rights price data. As shown in Fig. 1, we compared the transaction data of seven pilots from June 17, 2013 to December 31, 2017. It was found that although the China Hubei Emission Exchange is not the earliest experimental carbon emission pilot in China, since the beginning of its operation, the total volume and total amount have been the largest among seven carbon emission trading pilots. In addition, there are fewer trading days without trading volume.

(2) *Energy price*. The daily closing price of continuous coking coal futures (JM0) was selected [39]. This is because the CO_2 emission is directly related to the use of energy [40]. Energy-related variables mainly include oil, gas, and coal price levels and fuel switching from gas to coal [41]. In China's energy consumption structure, the proportion of coal is relatively large, and the carbon content of coal in fossil fuels is relatively high [21], which has a relatively large impact on carbon dioxide emissions.

(3) *Macroeconomic indicators*. The Shanghai and Shenzhen 300 Index (HS300) [42] was selected to reflect China's macroeconomic development level. Macroeconomic activities have a certain influence on the carbon emission rights market. As China's capital market continues to improve, the stock index can better reflect the fundamental situation of the economy [43]. Therefore, we select the Shanghai and Shenzhen 300 Index as an indicator of macroeconomic indicators.

The Shanghai Industrial Index (000004.SH) [44] was selected to reflect the speed of China's industrial development. This is because the departments that need carbon emission rights are usually industrial sectors. If the macroeconomic development becomes more booming, the carbon emissions of the industrial sector will also increase, and the demand for carbon emission rights will increase [21]. Therefore, we select the industrial index as another indicator of the macroeconomic indicators that affect the price of carbon emission rights.

(4) *Air quality*. We select the Air Quality Index (AQI) [45] where the exchange is located (Wuhan, China). The development of carbon emissions trading in China is closely related to the increase in air pollution in recent years. The degree of air pollution can be used as a direct indicator of carbon emissions, that is, air quality represents a certain degree of industrial emissions, and GHG or considerable levels of carbon dioxide emissions increase [46]. Therefore, we select the Air Quality Index of Wuhan City, the seat of the China Hubei Emissions Exchange, as an air quality indicator.

The above indicators are selected during the period of April 2, 2014–November 30, 2017. The trend of variables can be made more linear. Therefore, we perform logarithmic processing on all data. After taking the logarithm, the variable name is as follows (graphs of the original series and the logarithm series of these selected indicators are presented in the Appendix).

$lnHBEA = \log(HBEA)$, $lnJM0 = \log(JM0)$, $lnHS300 = \log(HS300)$, $lnSH = \log(000004.SH)$, $lnAQI = \log(AQI)$.

This section uses VAR-VEC model. Before fitting the model, we first test the stationarity of the sequence. Here we use Augmented Dickey–Fuller (ADF) unit root test [47]. Since the selected variables are price or climate indicators, they do not usually rise or fall with time, so there is no time trend for these variables. Therefore, no time trend was added when using the ADF test. The test results of the stationarity of the original sequence are shown in Table 1.

From the test results in Table 1, it can be seen that the P value of the original sequence is greater than 0.05, so all sequences are non-stationary sequences. This requires a first-order difference for all sequences. All first-order differential sequences are shown in Fig. 2.

From Fig. 2, we can initially find that these first-order difference sequences are stable. Then, the ADF test is performed again. The results of the stationarity test for the first-order difference sequence are shown in the second half of Table 1.

Table 1
ADF test results of original sequence and first-order differential sequence.

Variables	Test statistic	5% critical value	P value (original sequence)	Stability (original sequence)	P value (first-order differential sequence)	Stability (first-order differential sequence)
lnHBEA	−1.980	−2.860	0.2955	Non-stationary	0.0000	Stationary
lnJM0	−0.510	−2.860	0.8900	Non-stationary	0.0000	Stationary
lnHS300	−1.870	−2.860	0.3462	Non-stationary	0.0000	Stationary
lnSH	−2.027	−2.860	0.2748	Non-stationary	0.0000	Stationary
lnAQI	−2.524	−2.860	0.1098	Non-stationary	0.0000	Stationary

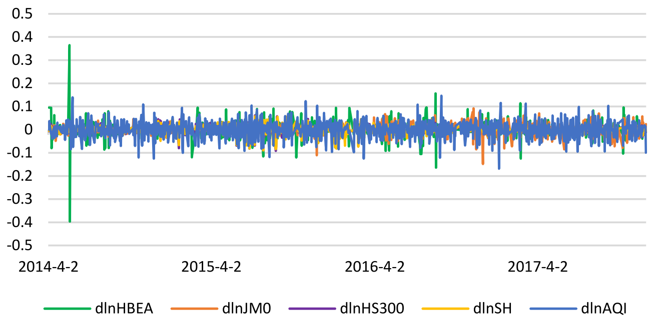

Fig. 2. First-order difference series.

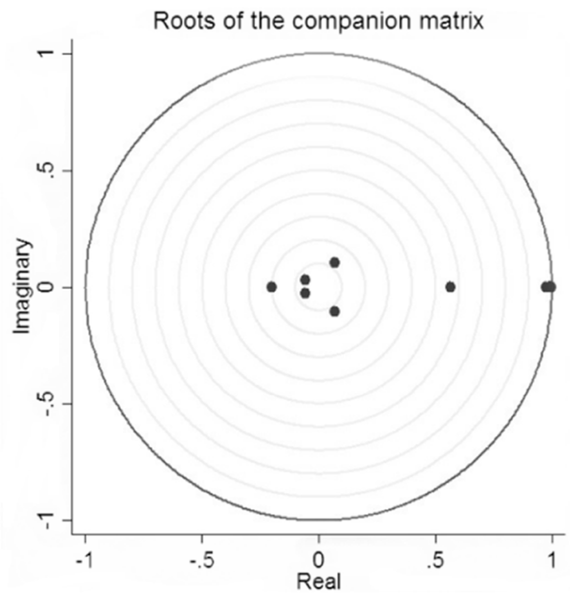

Fig. 3. Stationarity test result of the VAR model.

According to the ADF test results in Table 1, all the sequences are first-order single integer sequences, and a VAR model can be established. Before building the model, we first select the optimal lag order for the VAR model. The lag order selection criteria includes Likelihood Ratio (LR) test, Akaike Information Criteria (AIC), and Schwarz (SC) [48]. After comparing the AIC value and the SC value with other criterion test values, we choose the optimal lag order as 2 (optimal lag test results for the VAR model are given in the Appendix).

After determining the optimal lag order, we build a VAR model. Next, it is necessary to examine the stationarity of the VAR model to determine if the VAR model we built makes sense. If the VAR model is stable, subsequent analysis can be performed. The stationarily test result is shown in Fig. 3.

From Fig. 3, we can see that the reciprocal of the modulo roots of the VAR model is less than 1, that means all these values are within the unit circle, and the VAR model is determined to be stable. Therefore, subsequent analysis can be performed.

Table 2
Results of the Johansen cointegration test and largest eigenvalue test.

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	Max statistic	5% critical value
0	5	9209.5012	.	264.9269	227.9336	68.52
1	14	9323.468	0.22439	36.9933*	21.1632	47.21
2	21	9334.0496	0.02332	15.8301	12.0701	29.68
3	26	9340.0847	0.01337	3.7600	3.5921	15.41
4	29	9341.8807	0.00400	0.1679	0.1679	3.76
5	30	9341.9647	0.00019	–	–	–

According to the previously selected optimal lag order, we perform cointegration tests on all sequences. The results of Johanson Cointegration Test [49] and largest eigenvalue test are shown in Table 2.

The test results in Table 2 show that when rank = 0, the value of the trace statistic is greater than the critical value of 5%, thus rejecting the null hypothesis that there is no cointegration relationship. When rank = 1, the value of the trace statistic is less than the critical value of 5%, and therefore the null hypothesis that there is one or less than one cointegration relationship cannot be rejected. At the same time, the maximum eigenvalue test results in Table 2 are consistent with the trace statistics. Both test results can reject the null hypothesis that there is no cointegration relationship, but cannot reject the null hypothesis that there is one or less cointegration relationship. Based on these results of the Johanson cointegration test and the maximum eigenvalue test, the number of cointegration relations can be determined as 1.

According to the determined lag order and cointegration test results, the VEC model is fitted to the sequence. The standardized cointegration equation is as follows.

$$\begin{array}{l} lnHBEA = -0.093lnJM0 - 2.781lnHS300 + 3.085lnSH + 0.996lnAQI - 2.38 \\ \qquad\qquad\quad (0.0986) \qquad (0.5833) \qquad\quad (0.6349) \qquad (0.0589) \end{array} \tag{18}$$

From the cointegration equation, it can be seen that the Industrial Index has the greatest impact on the price of carbon emission rights, with a coefficient of 3.085. The Industrial Index is an indicator reflecting the speed of industrial development. Industrial development affects carbon emissions [21]. Rapid industrial development means that carbon emissions will increase accordingly, which will increase the demand for carbon emission rights in the carbon market. With the supply unchanged, the price of carbon emission rights will rise.

The impact of the Shanghai and Shenzhen 300 Index on carbon emission price is second only to the Industrial Index, with a coefficient of −2.778. The negative coefficient may be due to the fact that, the rapid development of the macro economy is accompanied by an increase in environmental and climate issues, so the government will increase efforts to encourage green and low-carbon economic development models. Driven by such policies, the carbon trading market will receive corresponding attention and development. Therefore, more enterprises and quotas will enter the carbon trading market, and the carbon emission price will decline. In addition, macroeconomic development has led to an increase in the volume of transactions, the gradual maturity of the trading system, and the lower transaction costs in the carbon market, which will also result in lower carbon emission price.

The Air Quality Index has a small impact on carbon emission price, with a coefficient of 0.996. This may be due to the increase in the Air Quality Index and the deterioration of air quality. Related policies will tend to control GHG emission to improve air quality. This will lead to a certain increase in the carbon market demand, carbon emission price will rise.

The impact of coal price on carbon emission price is minimal and the coefficient is only −0.993. The negative coefficient may be due to the fact that as coal price rise, coal consumption will decrease. With constant total consumption, this will increase the consumption of other fossil energy sources. Due to the highest carbon content of coal, the corresponding carbon emissions will decrease and the carbon emission price will decline.

The VEC model's estimation equation for *HBEA* is as follows.

$$\begin{array}{l} D(lnHBEA) = -0.02(lnHBEA(-1) + 0.093lnJM0(-1) + 2.781lnHS300(-1) \\ \qquad\qquad\qquad -3.085lnSH(-1) - 0.996lnAQI(-1) + 2.38) - 0.0004 \end{array} \tag{19}$$

The adjustment coefficient of the VEC model is −0.02, which indicates that when the *lnHBEA* is too high and deviates from the long-term equilibrium value, it will slowly decrease towards the long-term equilibrium value. However, the absolute value of the adjustment coefficient is smaller, the long-term adjustment is weaker, and the cycle of ironing is longer. The reason may be that China's carbon emission trading market is still in its infancy. The relevant system is not perfect, and its market function has no obvious effect. Information or price fluctuations in other markets cannot be quickly and effectively transmitted to the carbon emission trading market.

After fitting the VEC model, we need to test the stationarity of the model, so that we can know whether the inferences we made before have reference significance. The stationarity test of cointegration equation is shown in Fig. 4.

As shown in Fig. 4, in addition to the unit roots assumed by the model itself, the eigenvalues of the adjoint matrix all fall within the unit circle, indicating that the cointegration equation is stable, and the VEC model fitting results have reference significance.

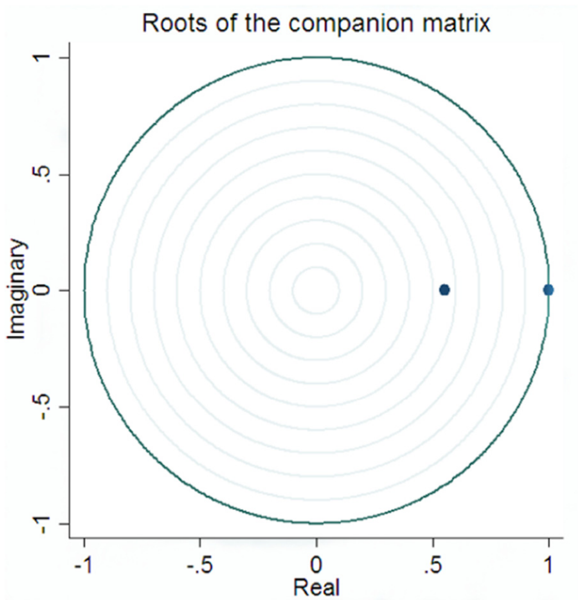

Fig. 4. Stationarity test of cointegration equation.

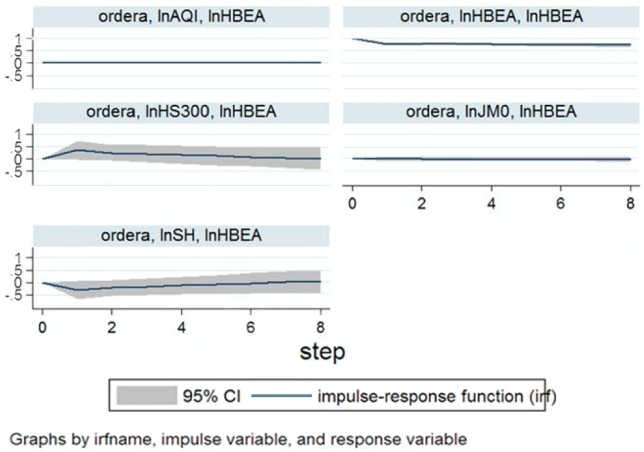

Fig. 5. Results of the IRF.

Finally, the IRF was used to study the dynamic relationship between carbon emission rights price and coal price, the Shanghai and Shenzhen 300 Index, the Industrial Index, and the Air Quality Index, to understand how carbon emission price react to the impact of other variables. Specifically, the IRF describes the impact on the current and future values of endogenous variables after imposing a standard deviation magnitude shock on the random error term. The corresponding result of the pulse is shown in Fig. 5.

From the results of the impulse response, it can be seen that the impact of coal price and Air Quality Index on the carbon emission price is very weak. The carbon emission price is mainly affected by itself. Positive impact of lnHBEA causes lnHBEA to rise, and this effect will decrease over time. The Shanghai and Shenzhen 300 Index and the Industrial Index have a positive and negative impact on the carbon emission price respectively, and gradually approach zero after the second period. This shows that among the selected indicators, the level of economic and industrial development as well as the rise and fall of carbon emission price themselves have a certain degree of prior indication of future changes in carbon emission price, and can be used as a reference factor in the study of carbon emission price.

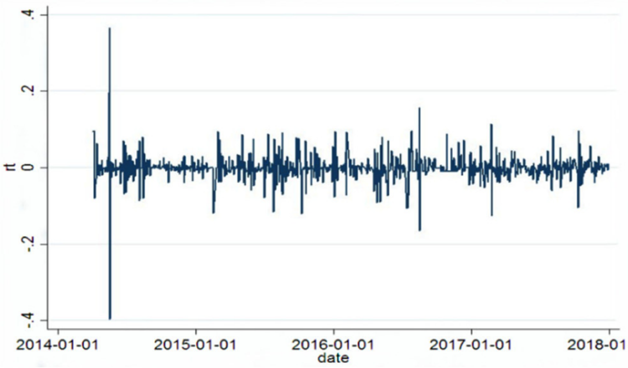

Fig. 6. Return series.

Table 3
Results of the distribution characteristics of the return series.

Statistical indicators	Statistics
Sample capacity	918
Mean value	−0.0003689
Standard deviation	0.0350529
Skewness	−0.3879878
Kurtosis	38.2017
JB test value	17043.96
P value	0.00000

Table 4
Results of stationarity test of the return series.

Return series	Test statistic	1% critical value	5% critical value	10% critical value	P	Stability
r_t	−38.549	−3.430	−2.860	−2.570	0.0000	Stationary

4.2. Fluctuation characteristics of carbon emission price

Next, we study the fluctuation characteristics of carbon emissions price. In this section, we still select the HBEA daily closing price [38] from China Hubei Emission Exchange as the carbon emission rights price data. The data is selected during the period from April 2, 2014 to December 30, 2017. To investigate the fluctuation characteristics of carbon emission trading price, we select the daily return rate as an indicator to reflect the fluctuation of the carbon emission price. The calculation of the rate of return series uses the logarithmic rate of return, which is the first-order difference of the logarithm of the closing price of each two consecutive trading days. It is calculated as

$$r_t = ln\frac{P_t}{P_{t-1}} \tag{20}$$

where r_t represents the daily rate of return, and P_t represents the closing price of the trading day t. Mapping the rate of return series, it can be initially determined that there is a certain degree of fluctuation aggregation (see Fig. 6).

Then we examine the distribution characteristics of the return series of carbon emission price to test whether the return series fits the conditions for fitting the GARCH model. The results are shown in Table 3.

According to the results in Table 3, it can be seen that the mean value of the return series is negative and close to 0, indicating that the overall price of the HBEA is gradually declining, and the fluctuations are characterized by fluctuations in the financial time series, aggregation and explosiveness. The skewness is negative, which indicates that the return series is left-biased. The kurtosis is much greater than 3, which indicating that the distribution features of "spikes and thick tails" are met. The P-value of JB test is less than 0.05, which indicates that the return series accords with the non-normal distribution.

Through the above analysis of the test results in Table 3, it can be concluded that the HBEA return series basically conforms to the characteristics of fluctuating aggregation, non-normal distribution and spikes and thick tails. In other words, this return series is suitable for building GARCH models.

Then it is necessary to test the ARCH effect of the return series. Before performing the ARCH test, we first test the stability of the return series, as shown in Table 4.

According to the results of the stationarity test of the return series, the statistic of the unit root test of the rate series is less than the critical value at the 1% significant level. Therefore, the original hypothesis of "existing unit root" can be

Table 5
Results of ARCH test of the return series.

Lag order	chi2	df	Prob > chi2
1	210.860	1	0.0000

Table 6
GARCH family models estimation results for the return series.

GARCH models	GARCH	TGARCH	EGARCH
Constant term (ω)	−0.0005803	0.0010026	0.0006687
ARCH term (α)	0.7941102	0.3827581	−37.79859
Asymmetric term (γ)	–	0.9553126	0.7653341
GARCH term (β)	0.1604046	0.138553	197.4103

Table 7
Comparison of the fitness of GARCH family models.

GARCH models	GARCH	TGARCH	EGARCH
AIC	−393.850	−395.939	−381.907
BIC	−391.921	−393.528	−379.979

rejected at the level of 1%, which means that the return series is stable and the following analysis can be carried out. Next we test the ARCH effect on the return series.

When conducting the ARCH test, we first use least-squares regression (OLS) to fit the return series to a model that only includes a constant term. Then use Engle's Lagrange-multiplier test to see if there is an ARCH effect. The ARCH-LM test results are shown in Table 5.

According to the ARCH test results, we can reject the null hypothesis without the ARCH effect at a significant level of 5%, which means that there is an ARCH effect in the return series.

Next, the GARCH family model is fitted to the return series. We fit the GARCH, TGARCH, and EGARCH models to the return series. Estimated results are shown in Table 6.

From the estimation results of the GARCH model in Table 6, it can be seen that the fluctuation persistence coefficient $(\alpha + \beta)$ of the yield series is 0.955, which satisfies the constraint that the coefficient is less than 1, and the value is very close to 1. This means that the impact of external information has a lasting impact on the series of returns. In other words, externally good news or bad news will have a long-term and persistent impact on Hubei carbon emission price fluctuations.

Based on the estimation results of the GARCH model, we continue to investigate whether there is asymmetry in the impact of good news or bad news on the return series. From the TGARCH fitting results in Table 6, the coefficient of the asymmetric term γ is 0.955, and the significance test can be used to illustrate the asymmetric effect of the fluctuation of the return series. It means that there is a leverage effect on the carbon emission rights price, and the bad news has a greater impact on the fluctuation of the return series than the good news.

From the EGARCH estimation results in Table 6, the coefficient of the asymmetric term γ is 0.765, but it fails the significance test. This shows that there is no asymmetry in the return series. However, since the coefficient is not 0 and greater than 0, a weak leverage effect can be considered.

Finally, we need to compare the fitting effects of these three GARCH family models. We use the AIC value and the Bayesian Information Criterion (BIC) value to compare the model's fitting effect. The smaller the value, the better the fitting effect. The comparison results are shown in Table 7.

From Table 7, it can be seen that among the three GARCH models, the AIC and BIC values of the TGARCH model are the smallest, which means that the fitting effect of TGARCH is slightly better. Therefore, we use the estimated parameters of TGARCH as the analysis result of the price fluctuation characteristics of carbon emission trading.

Based on TGARCH results, the sustainability coefficient $(\alpha + \beta)$ of the carbon emission rate series in Hubei is 0.521, which satisfies the constraint condition less than 1, but is not close to 1. This shows that the impact of external positive and negative information will not have a lasting impact on the profitability sequence, and the impact of external good news or bad news on the carbon emission rights price is within a short period of time. In addition, there is a positive leverage effect on the carbon emission price fluctuations in Hubei. Each time there is one good news, it will have 0.383(α) times impact on the yield series. Each time one bad news occurs, it will have a 1.338$(\alpha + \gamma)$ impact on the yield series. This shows that the same bad news will have a greater impact on carbon emission price fluctuation than good news.

5. Conclusions and policy implications

Based on the data of China Hubei Emission Exchange, this study investigated the influencing factors and fluctuation characteristics of China's carbon emission rights price. First, we used the VAR-based VEC model to explore the dynamic relationship between the four indicators of energy price, two macroeconomic indicators, air quality, and the carbon emission pricing price. The results showed that there was a long-term equilibrium relationship between the carbon emission price and coal price, Industrial Index, Shanghai and Shenzhen 300 Index, and Air Quality Index. When the carbon emission price is too high and deviates from the long-run equilibrium value, it will slowly decline toward the long-term equilibrium value. However, the absolute value of the adjustment coefficient is smaller, the long-term adjustment is weaker, and the cycle of ironing is longer. This may be due to the fact that China's carbon trading market system is still incomplete, and there are deficiencies in information disclosure, market supervision, and punishment violations. These problems have caused some of the information to be easily distorted and the information transmission was lagging behind, so that the interests of investors were not guaranteed.

Moreover, among these selected indicators, the Industrial Index in the macro economy has the greatest impact on the price of carbon emission rights. The Shanghai and Shenzhen 300 Index in the macro economy has the second largest impact on the carbon emission price. This shows that the current price of carbon emission in China is greatly affected by the macroeconomic conditions. Rapid industrial development means that the amount of carbon emissions will increase accordingly, resulting in an increase in the price of carbon emission rights. With the rapid development of the macro economy, the carbon emission trading quota will increase accordingly, and the transaction costs of the carbon market will also decrease, which will cause the carbon emission price to drop. In addition, the Air Quality Index and coal price have a relatively weak impact on carbon emission price.

Next, we used the GARCH family model to study the characteristics of China's carbon emission price fluctuations, and found that the carbon emission price return series was consistent with the characteristics of financial time series such as fluctuation aggregates, spikes and thick tails, and non-normal distribution. Then, by fitting the GARCH, TGARCH, and EGARCH models respectively, we found that the positive and negative impact of external information on carbon emission price did not produce a long-term sustained response. The impact of outside good news or bad news on Hubei carbon emission rights price is within a short period of time. In addition, there is a positive leverage effect on the carbon emission price fluctuations in Hubei, and the same bad news will have a greater impact on carbon emission price fluctuation than good news. This may be due to the fact that the pricing mechanism for China's carbon emission rights market is still not perfect, and the lack of carbon financial derivatives has led to asymmetric price fluctuations. This will increase the company's participation in carbon trading costs, which will affect the enthusiasm of companies involved in carbon trading.

According to the above research results, we found that China's carbon emission trading market does not have a long transaction time, the marketization level is not high, and the market lacks liquidity. There is a serious time lag in the information transmission process in the market. The pilot carbon market has large price differences and lacks an effective pricing mechanism and financial derivatives. In addition, the carbon market is in its infancy, the system and related laws and regulations are not perfect, and adjustments to price fluctuations are weak. With the launch of the unified national carbon market, these issues are of great concern.

Based on the above research results, we propose the following policy implications. First, China's carbon trading market needs to improve the information disclosure system, strengthen market information transparency, and improve market liquidity. Moderate liquidity is the key to form a reasonable and realistic price and promote enterprises to actively participate in carbon emissions trading. Second, it needs to spend more efforts on improving the carbon emission pricing mechanisms and reducing market risks. At present, China's carbon trading market price fluctuates greatly, which increases the carbon trading costs of evolved enterprises. Therefore, it is necessary to improve the pricing mechanism, implement prediction on changes in carbon emission price, and conduct risk management. Finally, complete legal system is indispensable for the orderly implementation and healthy development of carbon emissions trading market. China should improve the related policy and regulation system based on the actual development situation of its carbon market, and at the same time learn from other countries' successful development experience in carbon market.

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Appendix

See Fig. A.1 and Table A.1.

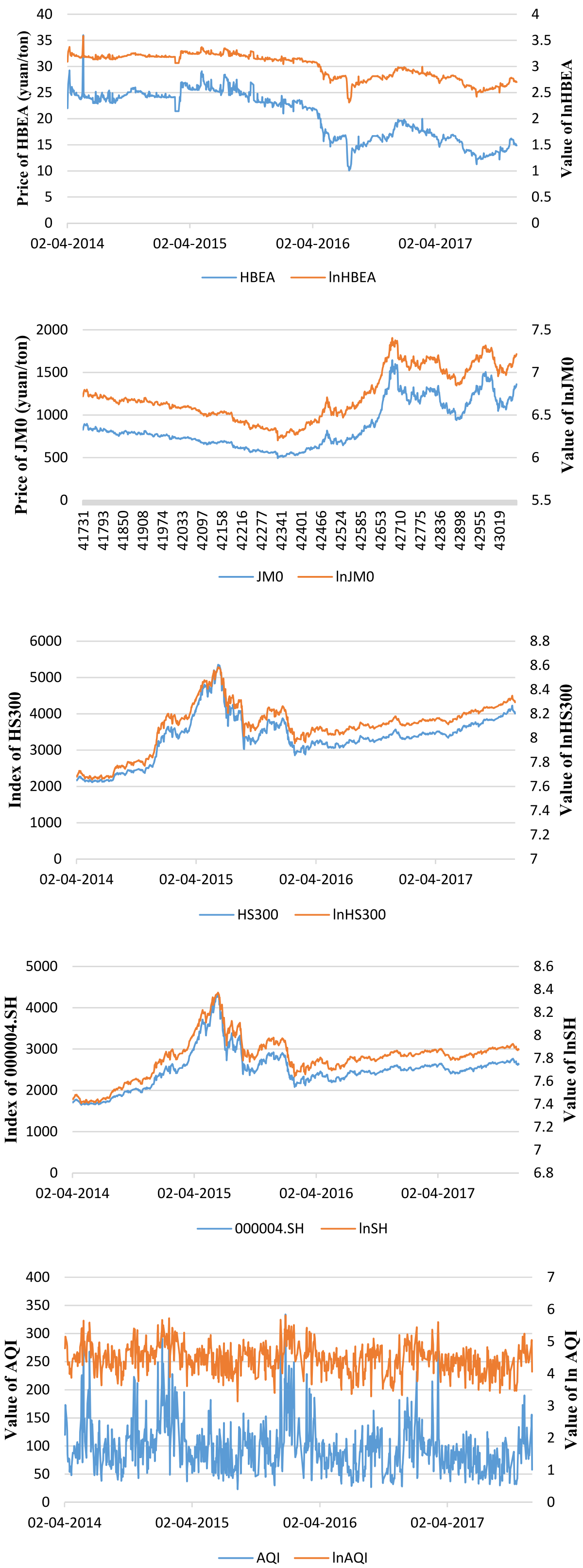

Fig. A.1. All of the original series and logarithm series.

Table A.1
Optimal lag test results for the VAR model.

Lag	LL	LR	p	FPE	AIC	HQ	SC
0	1555.44	–	–	2.1e−08	−3.46855	−3.4583	−3.44173
1	9320.01	15529	0.000	6.5e−16	−20.783	−20.7215	−20.6221*
2	9377.92	115.83*	0.000	6.0e−16*	−20.8566*	−20.7439*	−20.5616
3	9393.55	31.268	0.180	6.1e−16	−20.8357	−20.6717	−20.4065
4	9400.5	13.884	0.964	6.4e−16	−20.7953	−20.5801	−20.232

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